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IMAGE PROCESSING: RESEARCH OPPORTUNITIES AND CHALLENGES

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ABSTRACT. The need for advanced video surveillance systems that can detect anomalous behaviors has grown in response to rising crime rates and terrorist attacks. The research project's main goal is to design and create an Automated Video Surveillance (AVS) system that uses machine vision and image processing techniques to detect, monitor, and categorize objects of interest to improve security. The autonomous video surveillance system is structured in four steps to achieving this purpose, with each step handled as a separate phase. In Phase I, three distinct background subtraction methods are proposed for recognizing moving dynamic foreground objects in video picture sequences. Adaptive Kalman with Median Filter (AKM Model), Hybrid Model Combining Frame Differencing, Optical Flow, Gaussian Mixture Method (HFOM Model), and Wavelet Packet Based Model are the three approaches (WP Model). Phase II focuses on algorithms that improve the objects recognized by removing noise, correcting illumination and lighting change, and removing shadows. Self and projected shadows were both taken into account. For noise removal, an enhanced Morphological filter using Multiscale and Neighborhood-based Structural Element (MMNSE Filter) was proposed, and for illumination and lighting error correction, a Reflectance Model and Curvelet Transform based Illumination and Lighting Variation were Correction Algorithm (RCIC Algorithm) was proposed.
Index Terms: Automated Video Surveillance, Median Filter

INTRODUCTION

Security against terrorism (at both the national and international levels), as well as the protection of persons and property, has become a major global concern in recent decades and is given top attention by both the public and commercial sectors across the world. Technological advancements have prompted law enforcement agencies to expand their investment in security systems that can strengthen safety measures in response to such problems. This has permitted the implementation of several measures, including screening systems (for people and items), monitoring trusted person systems, biometric identity verification systems (fingerprint, face), and video surveillance. Law enforcement authorities employ the results of such technology to maintain social control and monitor and detect dangers to prevent criminal/illegal acts.

Video surveillance, a by-product of video technology and computer vision are becoming more important as a visual investigative tool among the different ways available (Kumar et al., 2008; Gaikwad and Narawade, 2012). It is one of the most widely used security technologies in the twenty-first century, allowing embedded picture capture from video data for anomaly detection. It is a current study topic that entails integrating digital computers with the surrounding environment to identify, recognize, and track things in the video to obtain knowledge about object behavior (people, cars, and animals). Increased knowledge of cutting-edge software and the low cost of digital video cameras has resulted in a significant number of video picture sequences that may be examined for recognizing objects and reporting suspicious occurrences.

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OVERVIEW OF VIDEO SURVEILLANCE

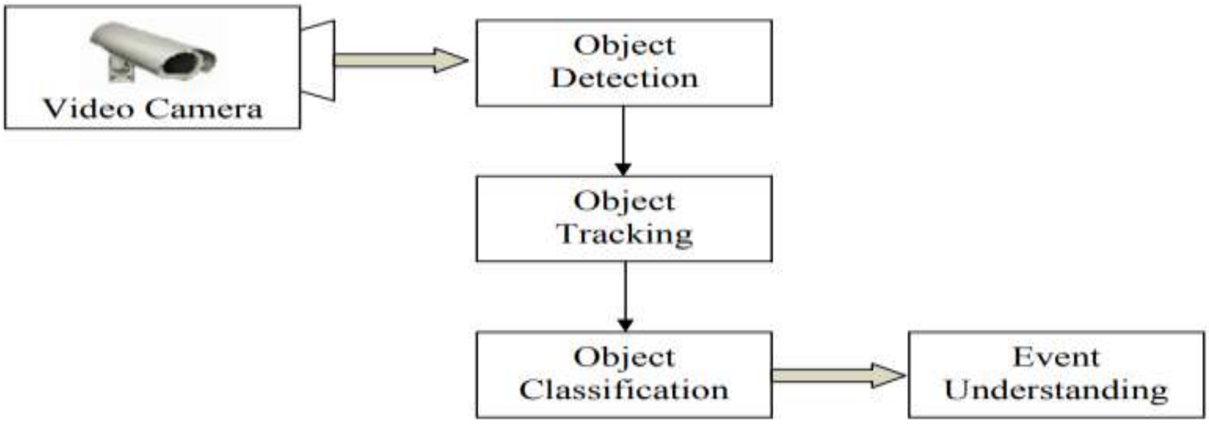

Figure 1.1: General Architecture of AVS

Low-level image processing approaches feed into tracking and classification algorithms, which feed into higher-level scene analysis and/or behavior analysis modules.

Object identification, tracking, and classification are the three subtasks that turn raw video picture sequences into intelligent information that can be utilized to comprehend events (Dee and Velastin, 2008).

OBJECT DETECTION

Detecting interesting items in the video is the first step toward automated surveillance, and this phase focuses on presenting solutions to this challenge. Object modeling and Object Detection are the two fundamental processes in object detection. Tracking Objects Classification of Objects Understanding the Situation Extraction of the foreground from a video camera (background subtraction). Object detection is accomplished by creating a 'background model' of the scene and then looking for deviations from the model for each input frame. Moving objects are defined as any substantial deviation from the backdrop model in an image region (foreground). These pixels are highlighted for further processing. Background subtraction of foreground extraction are terms used to describe this procedure. This technique produces the foreground picture containing the moving objects as a binary mask.

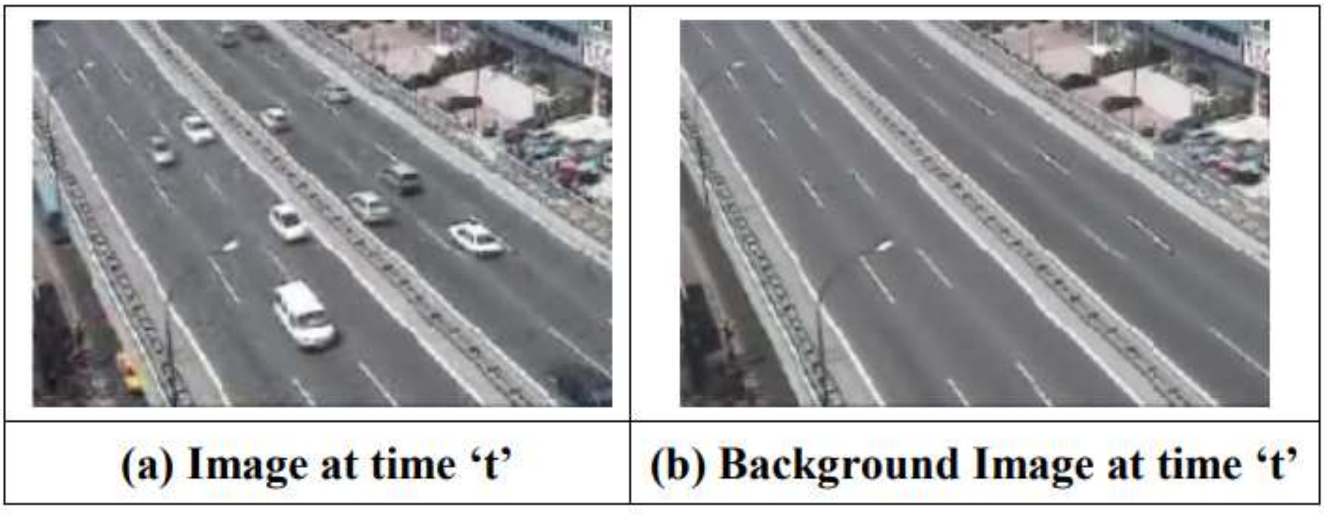

Figure 1.2: Background Subtraction – An Example

TRACKING OBJECT OF INTEREST

The next stage is to construct a temporal relationship between identified items from frame to frame after finding interesting things from a movie. This process is known as tracking, and it entails evaluating an object's trajectory as it travels across a scene. If the observed objects are continually visible and their form, size, and velocity do not change over time, this task can be deemed straightforward. However, in practice, this does not occur, and as a result, it is deemed extremely difficult. It's made even more difficult by the presence of several things in a scenario. Several Target Tracking (MTT) is the method of tracking multiple objects (Blackman, 2004). To establish the correspondence, a lot of effort has gone into devising appropriate matching algorithms and similarity measures, and in many situations, numerous object feature descriptors have been employed to increase the tracker's resilience and speed (Lei and Xu, 2006). Track initialization, track update, track split, track merging, and track deletion are the five essential processes in the tracking process. Only one track is linked with an item at any given moment in an AVS. When a new item is discovered and is not heavily connected with current tracks, a new track is created for that object. Continuous updating activities are conducted once a track is associated with an item.

CLASSIFICATION OF TRACKED OBJECTS

A surveillance system conducts several object categorization or classification tasks to create an intelligent analysis of the scene and to recognize distinct actions in a video sequence. Classification, also known as pattern recognition, discrimination, supervised learning, or prediction, is a process that entails the creation of a technique that maps data into one of several predetermined groups, according to Rokach (2009).

This work entails classifying identified things such as people, groups of people, vehicles, and animals in a generic context. In a military setting, this task may be more complex, requiring the identification of the vehicle type.

For the last three decades, researchers have explored object identification and classification tasks in both images and videos, finding that while recognition from a single picture is straightforward, it gets more difficult with video data. The AVS system uses this stage to identify object behavior and build high-level descriptions of their behaviors.

Object categorization is a critical component of smart surveillance systems, and the capacity to detect objects in pictures automatically is critical for a range of surveillance applications, including loss prevention in retail establishments, automatic identification of vehicle license plates, and more. In object categorization, the following qualities are desired (Chen et al., 2008b; Zhihua et al., 2009):

APPLICATIONS OF AVS

Security, law enforcement, and military agencies were the first to deploy video surveillance. Companies are now using it to defend their assets because of decreased equipment and interface expenses. It's increasingly commonly employed to track crimes (vandalism, theft, and assaults), with AVS serving as post-incident evidence. Many apartments and major stores use it to monitor entry to parking lots, pathways, and point-of-sale terminals (POS). AVS is just utilized for research reasons in this case. With sophisticated security restrictions, large-scale video monitoring may be found in transit networks, university campuses, business meetings, and Olympic games. In such cases, AVS employs numerous methods. Several government organizations and police forces have access to cameras and several monitors in case of an emergency (Javed and Shah, 2008).

DIFFERENT ARCHITECTURES OF AVS

AVS can be set up in one of two architectures: centralized or distributed. The emphasis of AVS in a centralized design is on the same location, and digital recorders are employed to gather all video sequences. A large computer server with massive computational capability is utilized for networking and analysis. The server should be capable of managing encoding as well as recording, storing, and

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viewing enormous amounts of video data. Because all traffic is directed to the server, centralized designs are typically bandwidth inefficient.
Distributed architecture, on the other hand, is geographically dispersed and employs several cameras. Extra processors, encoders, or network switches are required by the distributive design. In contrast to centralized architecture, which requires the transmission of the entire video sequence, they have the benefit of broadcasting just metadata retrieved from video. The distributive AVS design distributes resources and the central processing unit, lowering resource costs, and bandwidth requirements, and improving scalability.

PROPOSED ALGORITHMS

The suggested system, dubbed Video Surveillance System for Protecting People and Property (V2S3P), is comprised of the stages shown in Figure 1.3 and is meant to achieve the aforementioned principal purpose.

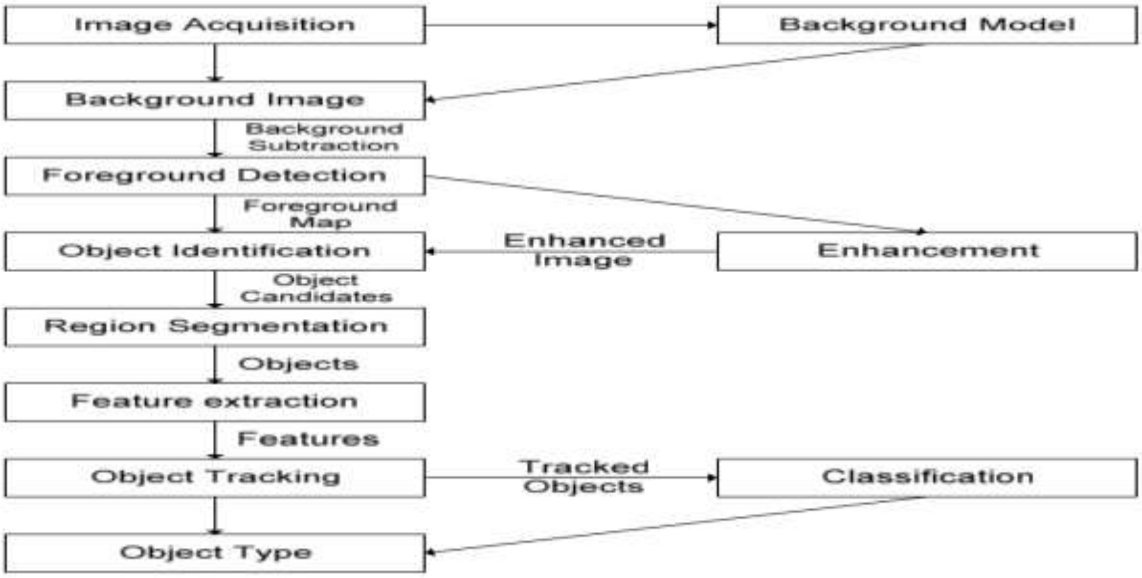

Figure 1.3: Algorithm Flow of V2S3P

Object detection is performed in the first stage utilizing three upgraded algorithms, and the research technique is meant to examine the three offered algorithms and choose the best one for object detection. These algorithms are hybrid algorithms, which combine the benefits of current widely used algorithms to improve the object detection process. The first algorithm (Adaptive Kalman with Median Filter - AKM Model) combines Kalman Filter with Median Filter, while the second algorithm (Hybrid Model Combining Frame Differencing, Optical Flow, and Mixture of Gaussian Method - HFOM Model) combines keyframing method with optical flow algorithm and color space background subtraction models.

The third approach (Wavelet Packet Based Model - WP Model) performs object recognition using wavelet packet modification with keyframing selection.

RESULTS AND DISCUSSION

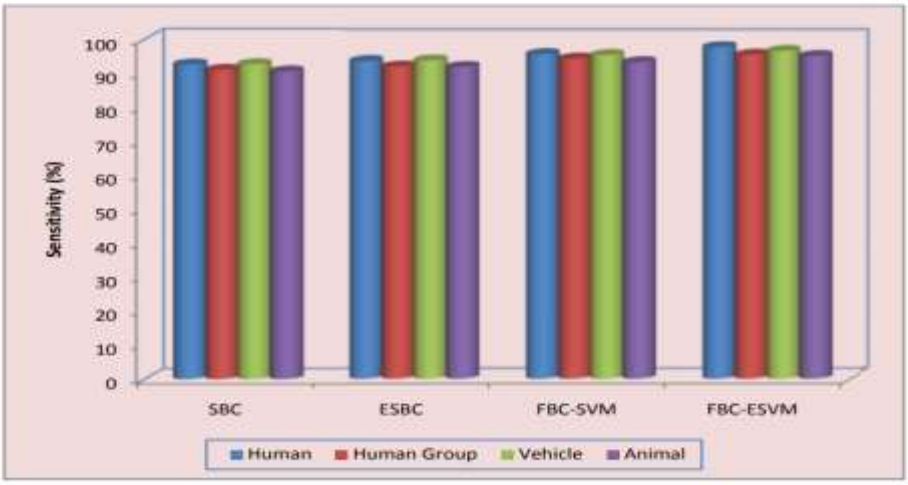

Figure 1.4: Sensitivity of Tracked Object Classification

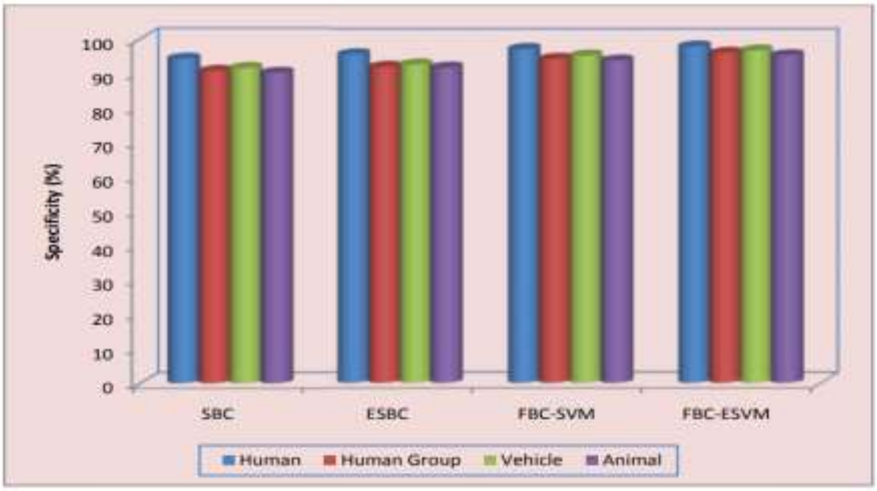

Figure 1.5: Specificity of Tracked Object Classification

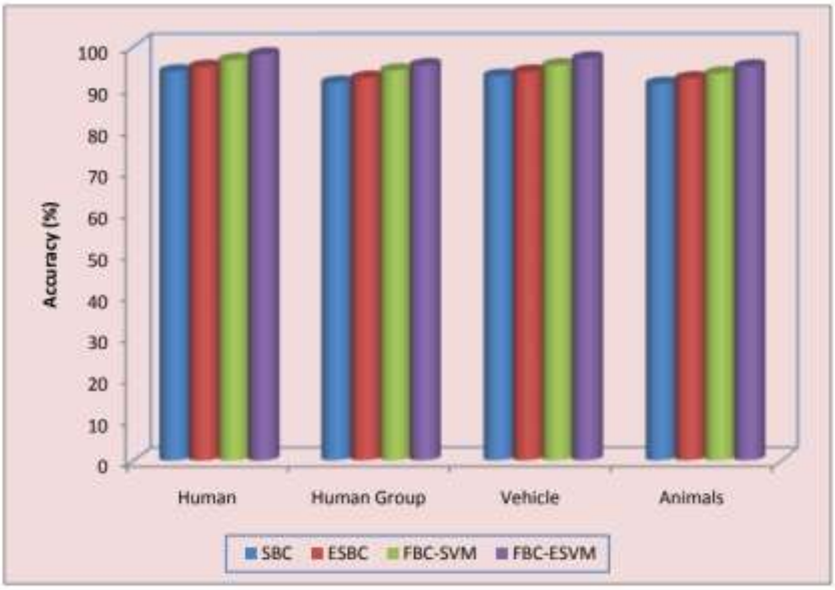

Figure 1.6: Classification Accuracy

Figures 1.4 and 1.5 show the sensitivity and specificity of the algorithms when presented with videos from the standard (VIRAT) and real video databases. These figures compare the conventional and proposed algorithms from the results, it can be deduced that the ability to identify humans, vehicles, and animals positively (sensitivity) and negatively (specificity) has improved with the use of the proposed ESBC and FBC-ESVM classifiers when compared to its existing counterparts.

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